Voter Cluster Analysis Report First Draft

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Introduction

LLM (Large Language Models) such as Google Gemini, Claude, ChatGPT, are increasingly deployed in domains that requires reasoning about human behavior, social dynamics, and political systems (Wikipedia, 2013). As AI has become part of everyday life in helping people draft emails, summarizing readings, answering questions, etc., these systems are also being increasingly asked to comment on political issues, including elections and voting behavior. Because democratic processes depend on informed public understanding, and the way LLMs reason about and predict voting patterns is not merely a technical issue, yet is a matter of civic importance. Thus, this raises an important question: **How do LLMs reason about voters and political preferences?**

Political prediction and voter modeling are central to campaigns, polling firms, advocacy organizations, and media outlets. In real world, demographic inference models are already used to understand, estimate, and predict elections. Age, race, education level, income, and geographic region are often used to estimate partisan leanings. If LLMs can accurately and responsibly reason about these patterns, then they could serve as a useful educational tools or assist in comparative political analysis. However, if they rely on oversimplified stereotypes or express high confidence in uncertain predictions, then they risk reinforcing misleading narratives. Because elections are foundational to democratic societies, the way AI systems handle politically sensitive information matters.

Recent research from the paper ”On the Dangers of Stochastic Parrots” argue that Large Languange Models can reproduce biases embedded in the training data and generate fluent language without true understanding (Bender, E., McMillan-Major, A., Shmitchell, S., & Gebru, T., 2021). This concern is relevant to voting behavior, such as when the models are asked to predict political preference (Democrat / Republican / Libertarian / many more), (Scot Wilson, 2020) from given voter's demographic information without recognizing nuance, regional variation, or change over time. Thus, this is prone to stereotyping and overgeneralization.

Beyond academic research, real-world concerns about AI and elections have grown. Policymakers have warned about the role of generative AI in spreading misinformation or shaping public perception during election cycles (Yan, H. Y., Morrow, G., Yang, K.-C., & Wihbey, J., 2025). If a user asks an LLM, "How would this type of voter likely vote?", the answer may appear authoritative, even if it is speculative. This makes it crucial to understand not only what predictions models make, but how they communicate uncertainty.

This project focuses specifically on how an LLM reasons about voting behavior under different informational conditions. Instead of only testing whether the model leans toward one political party, the study examines how it handles varying levels of detail and ambiguity. The prompts are designed to examine:

- How the model predicts voting preferences based on demographic information.
- Whether it changes its prediction when information is limited.
- Whether it gives consistent answers to the same prompt.
- Whether a single response is accurate and well-calibrated.

Voter ID	County	Age Group	Gender
004	Yakima	18-24	Male
005	Snohomish	55-64	Male
006	King	55-64	Female
007	Pierce	55-64	Male
008	Pierce	35-44	Female
009	Snohomish	35-44	Unknown/Other

Table 1: **sim_wa_voters** sample

Rather than simply asking whether the model is "correct" in a polling sense, this study focuses on the model's accuracy and consistency, as well as determining which variables (voters' information) most influence its predictions.

As LLMs become more integrated into how people access political information, it is important to understand what they predict, how consistently they do so, and what factors drive those predictions. This study aims to provide insight into the reliability and underlying reasoning patterns of LLMs in the context of voting behavior.

Experimental Design

For this experiment we have two main research questions:

1. How accurate are the predictions made by the LLM?
2. How does the consistency of predictions change when changing both the covariate levels and the covariates provided?

Research Question 1: Accuracy

To test the accuracy of the predictions, we use data from the Washington Secretary of State office (Reports, Data, and Statistics — WA Secretary of State, 2024). Their government website contains publicly available data related to voter registration, election results, and voter demographics for every year dating back to 2007.

The first step of using this data was to collect demographic information about real Washington voters and use it to create simulated Washington voters. In particular, we used the *Voter Demographics* tables from the *Voter Registration* data. Among this data, we focused on the covariates **County, Age, and Gender**.

To simulate $N = 100$ voters:

1. Sample a county for each voter, using the proportion of voters in each county as probability weights.
2. Use the two-way tables from the *County and Age group* and *County and Gender* data sets to calculate the conditional probabilities $P(\text{age group}|\text{county})$ and $P(\text{gender}|\text{county})$.
3. Sample an age group and gender for each voter, using the above conditional probabilities as probability weights.

The resulting data frame from this simulation will provide us with **sim_wa_voters**, our simulated Washington voters data. A sample of this data can be seen in Table 1.

This data will then be given to each question to generate responses.

The first group of questions relate to party voting habits:

- What party is this voter likely to vote for in the next U.S. presidential election?

- Is this voter likely to vote democrat in the next U.S. presidential election?
- Is this voter likely to vote republican in the next U.S. presidential election?
- Is this voter likely to vote third party in the next U.S. presidential election?

The variation in these questions will provide insight into how the LLM responds when the wording of the question varies. These questions about which party each voter will vote for will provide an understanding of how the LLM interprets general voting behavior based on the given characteristics.

The second group of questions relates to specific items on a ballot. Each question was taken from the Washington 2024 General Election ballot (2024 General Election Voters' Guide — WA Secretary of State, 2024):

1. Federal Candidates
   (a) President/Vice President
   (b) Maria Cantwell or Dr Raul Garcia for U.S. Senator for Washington State
2. Statewide Candidates
   (a) Sal Mungia or Dave Larson for Supreme Court Justice Position #02
   (b) Bob Ferguson or Dave Reichert for Governor
   (c) Mike Pellicciotti or Sharon Hanek for State Treasurer
   (d) Pete Serrano or Nick Brown for Attorney General
3. Measures
   (a) Initiative Measure No. 2066 (concerns regulating energy services)
   (b) Initiative Measure No. 2109 (concerns taxes)
   (c) Initiative Measure No. 2117 (concerns carbon tax credit trading)
   (d) Initiative Measure No. 2124 (concerns state long term care insurance)

These questions will provide insight into how the LLM predicts specific voting behavior, with regard to federal and state voting, based on the given characteristics.

Given the simulated voter data, we then prompted the Google Gemini *gemma-3-27b-it* model to predict how each voter would respond to each question in both groups of questions.

Research Question 2: Consistency

To test the consistency of the predictions, we simulate voters with a wider range of covariates than we used to test accuracy. In particular the covariates we used were race, age, gender, urbanicity, marital status, number of kids, religion, education, and income.

Levels of each covariate were sampled uniformly to simulate $N = 100$ voters. Voters were also assigned a voter ID.

We then grouped the covariates into **demographics** (race, age, gender, urbanicity), **family** (marital status, number of kids, religion), and **socioeconomic status** (education, income). For each group we created a sub-data frame containing only the covariates for the respective group and the voter ID.

Each data frame will then be given to each question to generate responses.

For consistency testing we add several more questions in addition to those used for accuracy testing.

We add a group of questions taken from a political typology quiz from the Pew Research Center (Pew Research Center, 2021):

- Would this voter rather have small government providing fewer services or bigger government providing more services?
- Does this voter think 'Business corporations make too much profit' or 'Most corporations make a fair and reasonable amount of profit'
- Which comes closer to your view of candidates for political office, even if neither is exactly right? There is at least one candidate who shares most of my views. None of the candidates represent my views well.
- Which of the following statements comes closest to your view? Religion should be kept separate from government policies Government policies should support religious values and beliefs

These questions provide a more comprehensive view of political ideology than those used in the accuracy testing. We are able to use such questions as we are not limited to questions in which we have real data for.

We also ask, "Is the behavior easy to predict?" for each voter. This question will give us a sense of how much the model believes it understands the voters.

Using the same Google Gemini *gemma-3-27b-it* model as before, we provide the voter data each question as a prompt to the model. We then have the model predict a response for the entire data set five times, resulting in 5 predictions per voter, per question.

Input and Output

To format the prompts, we have to modify the questions to ensure the output is providing the desired results in a format we can work with.

Each question is of the form:

Voter data (voter_id, county, age, gender): *data frame.* For each voter in the voter data, *question* Respond with only *response options.* Can only return unknown sparingly: voter id. prediction

Where *data frame* contains every voter and their covariate information, and *response options* contains the appropriate responses for each question. The output will then return a list containing the prediction for each voter with the respective voter id for identification.

Example prompts:

1. Voter data (voter_id, county, age, gender): 1, King, 55-64, Male; 2, Kitsap, 25-34, Male; 3, Thurston, 45-54, Male. For each voter in the voter data, what party is the voter likely to vote for in the next U.S. presidential election? Respond with one word, yes no. Can only return unknown sparingly: voter id. prediction
2. Voter data (voter_id, marital_status, num_kids, religion): 1, widowed, 1, Prefer not to say; 2, widowed, 1, Prefer not to say; 3, married, 4+, Sikh. For each voter in the voter data, would the voter vote for Bob Ferguson or Dave Reichert for Governor in Washington State, in the 2024 general election?, Respond with only the first name of the candidate. Can only return unknown sparingly: voter id. prediction
3. Voter data (voter_id, race, age, gender, urbanicity, marital_status, num_kids, religion, education, income): 1, White, 18-24, unspecified, urban, widowed, 1, Prefer not to say, bachelor, <$25k; 2, Black/African American, 65+, nonbinary, rural, widowed, 1, Prefer not to say, graduate/professional, <$25k. For each voter in the voter data, which of the following statements comes closest to their view? A: Religion should be kept separate from government policies, B: Government policies should support religious values and beliefs. Respond with only A B. Can only return unknown sparingly: voter id. prediction

Example output for prompt 1:

1. yes
2. no
3. yes
4. no
5. yes
6. no
7. yes
8. no
9. unknown

References

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